# COMBATING SOCIAL ENGINEERING THREATS IN MOBILE DEVICES: COMPARATIVE ANALYSIS OF EMERGING THREATS, MACHINE LEARNING, AND USER AWARENESS IN AFRICA

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**ABSTRACT:** Mobile devices are prime target for social engineering attacks, posing significant threats to user privacy and security. Particularly in Africa where cybersecurity measures lag behind adoption rates. This study provides a comparative analysis of vulnerabilities, attack vectors, and cutting-edge solutions for safeguarding mobile device users against the nefarious acts with a focus on Nigeria. Using a mixed-methods approach, we analyzed 12,000 attack samples from Nigeria's 2023 mobile banking Trojan outbreak. The data was supported by other security reports e.g, INTERPOL. Benchmarks were established to enable direct comparison of detection rates for African threat variants. Machine learning models were trained on localized features and evaluated using detection accuracy, adoption feasibility and scalability. The study revealed that ML-SMEPF has the high percentage in fraud detection globally with 40% better detection in Africa. We conclude that region-specific cybersecurity strategies, including voice-based multi-factor authentication and AI-driven endpoint protection, are critical for strengthening mobile security in Africa.

**KEYWORDS:** Mobile Security Threats, Mobile Device Users, Emerging threats, Social Engineering threats

## I. INTRODUCTION

Mobile device adoption in Africa has surged, with projections of 18.2 billion devices globally by 2025[1]. However, this growth has not been matched by robust cybersecurity measures, making the region a prime target for mobile-focused social engineering attacks. The rapid proliferation of mobile devices across Africa has transformed the continent into one of the fastest-growing digital ecosystems in the world, enabling unprecedented access to financial services, communication, and online resources. However, this surge in mobile connectivity has also created fertile ground for social engineering attacks, where cybercriminals exploit human psychology rather than technical vulnerabilities to deceive users. As mobile banking, mobile money platforms, and digital services become deeply embedded in daily life, Africa has witnessed an alarming escalation in threats such as phishing, smishing, vishing, SIM-swap fraud, mobile malware, and impersonation scams. These



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attacks disproportionately target users in regions with limited cybersecurity awareness, inconsistent regulatory enforcement, and widespread use of low-cost devices with weak security configurations. Traditional security controls—antivirus tools, signature-based detection, and rule-based systems—have proven increasingly inadequate against these evolving, human-centred attacks. Consequently, machine learning (ML) has emerged as a critical line of defence, offering dynamic threat detection through behavioural analysis, anomaly identification, and automated classification of malicious content. At the same time, studies show that even the most sophisticated ML systems cannot fully address social engineering risks without strong user awareness, digital literacy, and context-specific security training. This is particularly true in Africa, where cultural, linguistic, and socio-economic factors shape user behaviour and influence susceptibility to deception. The increasing number of attacks on mobile devices has created major concern, considering the widespread use of mobile devices. Nigeria, for example, ranked among the top ten African countries facing cyber threats in 2024 [69][7] and 19th globally [8]. The 2023 mobile banking Trojan outbreak in Nigeria, where attackers disguised malicious apps as legitimate banking tools., exemplifies this trend, leading to significant financial losses for individuals and organizations. While global solutions exist, they often fail to address region-specific attack vectors, such as scams delivered in Nigerian pidgin or USSD code injection. This study argues that effective defence requires localized strategies. This study therefore presents a comprehensive comparative analysis of emerging social engineering threats on mobile devices in Africa, the effectiveness of ML-based detection approaches, and the indispensable role of user awareness in mitigating these attacks. By examining real-world attack patterns, model performances, and behavioural weaknesses, the paper provides a contextualized understanding of how Africa can strengthen mobile cybersecurity through a combined framework of technology, education, and policy. We provide an in-depth analysis of current vulnerabilities and evaluate machine learning frameworks trained on African linguistic and behavioural data. Our research shows that such tailored approaches significantly outperform global security tools in detecting and preventing mobile social engineering threats in Africa.

## II. RELATED WORKS

The number of mobile users is increasing, and most users use lock screens, fingerprints, or facial sensors for protection. It seems that these protective measures are not sufficient, given the rise of threats posed by mobile attackers. In their studies, [10] and [11] concluded that many mobile users disregard other security best practices to protect their devices from threats. Cyber threats such as phishing are an online spoofing mechanism in which social engineering messages are communicated to users via electronic communication channels such as fake websites, emails, ads, antivirus, and scareware, among others, to perform tasks that are beneficial to attackers [12][13]. Phishing attacks are classified into several categories, including email, spear, whaling, vishing, interactive voice response, and pharming [14][15][16][17]. Email phishing attacks refer to the type of phishing where attackers send fraudulent emails that appear to come from reputable sources to steal sensitive information [18][17]. Sometimes, attackers send out bulk emails that appear to look like they are from a trusted source, such as popular online services. Once the users enter their details, the attackers capture them and use the information to mutate previous emails and read professional information about individuals or organizations [19][15]. Spear-phishing attacks can be seen as specific phishing that targets specific individuals or selected groups using their names to make claims that appear to come from trusted senders [20][15][21]. In this form of phishing, attackers research their targets and create personalized messages that appear to come from



Volume 1, Issue 4, 2025
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someone trusted by the target. This makes it difficult to distinguish them from legitimate communications, explaining the high success rate of these attacks compared to other social engineering techniques [23]. Whaling phishing is a spear-phishing attack targeting high-profile individuals within an organization, such as board members or individuals often tagged as big fish. Vishing attacks (voice phishing) refer to phone phishing to manipulate individuals to provide sensitive information for verification, such as calls from a bank or technological support [15]. Attackers use social engineering techniques to convince victims to provide sensitive information or to perform activities that compromise their security. Interactive voice response phishing is another type of phishing in which attackers use an interactive voice response system to make the target enter private information as if it were from a legitimate business [22][15]. Pharming phishing also refers to a situation in which attackers manipulate the DNS settings of legitimate websites, redirecting users to a fraudulent site without their knowledge. The fake site appears identical to the real site, and any information entered by the user is captured by the attackers.

There are several other types of phishing attacks, which include clone phishing, evil twin phishing, credential harvesting, ransomware phishing, watering hole attack, pop-up phishing, Smishing, Quid Pro Quo attacks, malware-based phishing, QR code phishing, social engineering phishing, and malicious AI [24][25][26]. Malware is an intrusive and disruptive program designed to operate on mobile devices or computers without the owner's knowledge or permission. It aims to gain unauthorized access to private data, disrupt device functionality, or even hijack resources for malicious purposes [70][27][28]. Often, Remote Access Trojans (RATs), Bank Trojans, Ransomware, Cryptomining Malware, Adware, and Spyware are referred to as types of malwares [29][30]. Remote Access Trojans (RATs) allow attackers to gain extensive access to data on the infected devices, including call history, SMS data, browsing history, and installed applications. Bank Trojans are disguised as legitimate applications for tricking on users to provide confidential financial information. Once any of these Trojans is activated, it saves the system information within itself or opens the infected mobile device or computers to access information remotely and send it via the Internet to another computer [30]. Sometimes, attackers use software to encrypt important files on users' mobile devices or computers, and demand a ransom to unlock them. This type of malware is referred to as a ransomware. Attackers build ransomware to discover any vulnerability in the user's system and generate a backdoor. The backdoor was used to deploy the ransomware and install it on the devices. This becomes passive when the user is offline and active when the device is connected to the internet. When the ransomware starts encrypting and blocking the user's data, the attackers start extorting the user by demanding ransomware in exchange for the encrypted data.

Crypto mining malware is another type of malware mostly used by attackers. This malware covertly uses the processing power of infected mobile devices or computers to mine cryptocurrencies without the user's knowledge. The Adware runs in the background of the system and settles on the devices without the consent or knowledge of the user [31]. This type of malware displays unwanted advertisements on a device, redirecting users to malicious websites [32]. Attackers use spyware to monitor and collect information about user activities. Social engineering is a broader term for manipulative tactics that bypass security. It is one of the oldest techniques that challenges the robustness of network firewalls, cryptography methods, intrusion detection systems, and antivirus software systems [15]. Social engineering attacks are the greatest threat to cybersecurity [33][34]. They can be detected but are difficult to stop completely [35][36]. Attackers take advantage of the targets to obtain sensitive information without any singular technical defensive strategies [37][38][24]. Social engineering attacks can be classified into



Volume 1, Issue 4, 2025
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several categories based on different perspectives, as demonstrated in [15], including the following.

i. Human-Based Attacks: Attackers are involved in direct interactions with a target to gather information. For instance, attackers pretend to be someone else to gain trust and confidence in extracting information from targets. This can also occur because of confusion or hoaxing by attackers [24].
ii. Computer-Based Attacks: Attackers use technology such as mobile devices or computers to obtain information from targets. For example, phishing. In this category, attackers use social engineering toolkits to spear phishing emails [39].
iii. Technical-Based Attacks: Attackers use digital means such as social networks or online services to gather the desired information from targets. An example of such an attack is spear-phishing, which is aimed at specific individuals or organizations.
iv. Physical-based attacks refer to physical actions performed by attackers to gather information. An example of such an attack is dumpster diving [40].
v. Social-Based Attacks: These attacks exploit social interactions and relationships to manipulate the targets. These attacks are the most successful and dangerous because they involve human interaction [41]. An example is baiting and spear-phishing.

Social engineering attacks can also be categorized based on the techniques used by attackers, such as psychological manipulation, phishing and variants, physical interaction, and digital deception. Another classification of social engineering attacks based on the attack lifecycle involves reconnaissance, engagement, exploitation, execution, and post-exploitation phases [42][43]. In view of the existing classification, [15] summarized the classification of social engineering attacks into two major categories. They classified it as either direct or indirect. Direct attacks include physical access, dumpster diving, phone social engineering, pretexting, impersonation, hoaxing, and stealing of sensitive information. Attacks that can be launched remotely via malware software are classified as indirect attacks. Unlike direct attacks, this does not require an attacker to launch an attack. Examples of these attacks include phishing, fake software, pop-up windows, ransomware, smishing, online social engineering, and reverse social engineering.

### A. Psychological Aspects of Social Engineering and Machine Learning (Behavioral) Based Analysis

Humans are naturally inclined to trust one another. This trust makes humans the weakest link in the security chain [15]. Many malicious activities have been accomplished through human interaction. This influences a person psychologically to divulge confidential information or break security procedures [44]. The overall goal of social engineering attacks is to prevent the target from acting rationally and act on emotions that can be manipulated, such as trust, fear, anger, sense of duty, sense of authority, vanity, philanthropy, friendship, patriotism, and urgency [24]. For instance, phishing attacks use urgent language to create a sense of immediate danger, thereby prompting victims to act quickly without proper scrutiny. Additionally, attackers may act as authority figures to exploit the human tendency to comply with perceived authority. The key psychological aspect that attackers exploit is cognitive bias, where individuals feel obliged to return favors or mimic the actions of others [45]. Owing to these human interactions, social engineering attacks have become the most powerful attacks that threaten all systems. However, the psychological impact of social engineering attacks can be profound, leading to feelings of guilt, embarrassment, and a loss of trust in digital systems. Machine learning (behavioral)-based analysis is the most focused area for detecting phishing threats, malware, and social engineering attacks.



Volume 1, Issue 4, 2025
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These detection methods are much more versatile and can detect changes in phishing sites than other detection methods. Machine learning can provide the ability to prevent threats when sufficient quality training datasets are provided [24]. The machine learning-based method is powerful in detecting threats but is largely dependent on the size and quality of the available training dataset and the hyper-parameters to obtain optimal accuracy [46].

Machine learning detects phishing threats, malware, and social engineering attacks primarily through classification. Research has been conducted on different machine-learning-based techniques, such as neural networks, decision trees, and support vector machines [47]. For example, in their study of machine learning-based mobile threat monitoring and detection, [48] conducted mobile threat monitoring and detection studies using ZeroR, OneR, Naïve Bayes, and J48 and found that the best classifier achieved 100% accuracy with a detection rate of 94.59%. [49] on the evolution of 5G networks highlighted the importance of mobile vehicle social networks (VSNs), which provided a new method of code propagation. The authors proposed ‘‘Machine Learning based Code Dissemination by Selecting Reliability Mobile Vehicles in 5G Networks’’ (MLCD) to select lower-cost codes and code spreading tools with high reliability and coverage. They concluded that by comparing the MLCD scheme with other schemes, it improves code propagation security by 83.6% and 18.86% with limited costs and the coverage rate of updated information by 23.16% in 5G networks. Also, [50] proposed a machine-learning-assisted secure mobile electronic payment framework (ML-SMEPF) to detect malware, fraud, and authentication issues in mobile transactions. The reliability of the framework was proven in a simulation performed based on the accuracy, safety, performance, and cost factor. Other studies, such as [51], developed a machine learning model called IntruDTree to detect cybersecurity threats. The effectiveness of the IntruDTree model was analyzed by comparing it with traditional machine learning methods. Several other models have been proposed, such as SMS Spam Detection and Classification System based on Fog Augmented Machine Learning [52], Vulnerability Identification System (AVIS) that can identify malicious applications in advance using the Naïve Bayes classification algorithm [53], and multi-criteria decision-making based mobile malware detection system using a risk-based fuzzy analytical hierarchy process approach to evaluate Android mobile applications [54].

## B. Secure Authentication Methods and Security Awareness and Training

To defend against phishing, malware, and social engineering attacks, individuals and organizations must implement robust, secure authentication methods. For instance, Multi-Factor Authentication (MFA) requires users to provide multiple forms of verification before accessing the system. Phishing-resistant MFA, which uses methods such as biometric authentication, hardware tokens, and cryptographic keys, offers enhanced protection by making it difficult for attackers to intercept or replicate authentication credentials [55]. Additionally, risk-based authentication adapts security measures based on the perceived risk level of each login attempt using the IP address, geographic location, and device recognition to determine the need for additional verification [56]. Advanced endpoint security solutions that include real-time threat detection and automated responses have become essential for organizations that aim to protect their digital assets from increasingly sophisticated attacks. These solutions leverage cutting-edge technologies such as artificial intelligence (AI), machine learning (ML), and behavioral analysis to identify and neutralize threats as they emerge. Unlike traditional antivirus software, which relies on signature-based detection, these advanced tools can detect zero-day exploits, fileless attacks, and other evolving threats in real-time [57]. For example, CrowdStrike Falcon employs AI-driven threat detection to provide



Volume 1, Issue 4, 2025
https://doi.org/10.5281/zenodo.17792985

continuous monitoring and rapid response, thereby significantly reducing dwell time and minimizing potential damage [58]. Similarly, Microsoft Defender for Endpoint seamlessly integrates with the Microsoft 365 ecosystem, offering advanced threat analytics and automated remediation capabilities [59]. These solutions not only enhance security, but also improve operational efficiency by reducing the burden on IT teams.

Another critical advantage of advanced endpoint security solutions is their ability to integrate with broader security ecosystems, such as Security Information and Event Management (SIEM) platforms and threat intelligence feeds. This integration enables organizations to adopt a holistic approach to cybersecurity, ensuring that threats are identified and addressed across all layers of the network. SentinelOne, for instance, provides autonomous endpoint protection that combines real-time threat detection with automated response features, making it a strong contender in the market [28]. Additionally, Trend Micro Apex One offers machine-learning-powered detection and centralized management, allowing organizations to enforce consistent security policies across all endpoints [60]. Social engineering attacks are the most powerful attacks that threaten all the systems. These attacks cannot be prevented using software or hardware solutions alone, as long as people are unaware of and trained to prevent these attacks. One of the most common ways to prevent phishing threats, malware, and social engineering attacks is to educate individuals to identify these attacks and protect themselves from falling. It is encouraging that most African countries, including Nigeria, have initiated public awareness campaigns, although predominantly online, to prevent cyber threats. Examples of such awareness campaigns include #YouMayBeNext, #JustOneClick, and #OnlineCrimeIsRealCrime. Occasionally, awareness campaigns occur in educational institutions [9]. Business organizations train their staff using different methods, such as games and simulated phishing emails [61][24]. These training methods have been proven to have a positive effect on detecting phishing threats, malware, and social engineering attacks [62]. Therefore, to counter evolving sophisticated phishing threats, malware, and social engineering attacks, attention must be focused on the awareness and training of people on the detection and prevention of these attacks. This can be expanded to capture governmental and non-governmental initiatives, individuals, and organizations.

## III. METHODOLOGY

This study employs a mixed-methods approach to analyze region-specific mobile threats and evaluate tailored defenses in Africa, with a focus on Nigeria.

### A. Data Collection and Preprocessing

Primary data consisted of 12,000 attack samples collected during Nigeria's 2023 mobile banking Trojan outbreak [7]. This dataset was supplemented by regional threat reports from INTERPOL [9] and global benchmarks from Kaspersky [3] and CrowdStrike [27] to enable a direct comparison of detection rates. The raw data underwent a standard preprocessing pipeline: Data cleaning was done to removed duplicate samples and non-malicious files; localized features were explicitly extracted. This include: linguistic cues to identify keywords and phrases in Nigerian Pidgin from SMS and app data; USSD command sequences and transaction logs from mobile money platforms were parsed to establish normal and anomalous patterns; and sender IDs, flash SMS flags, and network origin data were cataloged.

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Volume 1, Issue 4, 2025
https://doi.org/10.5281/zenodo.17792985

### B. Machine Learning Model Training

Two machine learning frameworks were implemented and tailored for this study. This include ML-SMEPF (Machine Learning-Assisted Secure Mobile Electronic Payment Framework) [50] and MLCD (Machine Learning-based Code Dissemination) [49]. Training parameters include:

i. Train-Test Split: A 70-30 stratified split was used to maintain the distribution of attack classes.
ii. Model Architecture: ML-SMEPF used a random forest classifier with 100 estimators; MLCD used a Gradient Boosting model.
iii. Hyperparameters: Optimized via rid search, focusing on maximizing the F1-score. Training was performed using the Scikit-learn library in Python.

### C. Evaluation Metrics

Models were evaluated against a commercial antivirus solution (used as a baseline) through A/B testing. Performance was measured using detection accuracy, precision, recall, F1-score, and False Positive Rate. Additionally, adoption feasibility and scalability were assessed qualitatively through case studies, including testing voice-based MFA with 50 low-literacy users.

## IV. RESULTS AND DISCUSSION

Our analysis confirms that Africa's mobile threat landscape is distinct, characterized by culturally adapted attacks that global solutions often miss. Table 1 summarizes these key differences.

**Table 1:** Social Engineering Attack Comparison: Global vs. African Variants

| SN | Attack Type | Global Characteristics | African Variants | Localized Detection Approach |
|---|---|---|---|---|
| 1 | Mobile Phishing | Generic bank impersonation [30] | Fake loan apps with local lender names | NLP trained on Nigerian Pidgin + SMS patterns |
| 2 | SMS Spam | Package delivery scams [52] | Urgent family help messages (+local numbers) | Carrier-level filtering for flash SMS |
| 3 | Banking Trojans | APK downloads [27] | USSD code injection + WhatsApp spreading | MLCD model [49] with USSD command database |
| 4 | Ransomware | Enterprise data encryption [4] | Mobile payment wallet locking | Behavior-based decryption |

As summarized in Table 1, social engineering attacks manifest differently across regions. Figure 1 further quantifies these disparities, showing phishing's dominance in Africa (62% prevalence) compared to global averages (45%).



Volume 1, Issue 4, 2025
https://doi.org/10.5281/zenodo.17792985

4.0

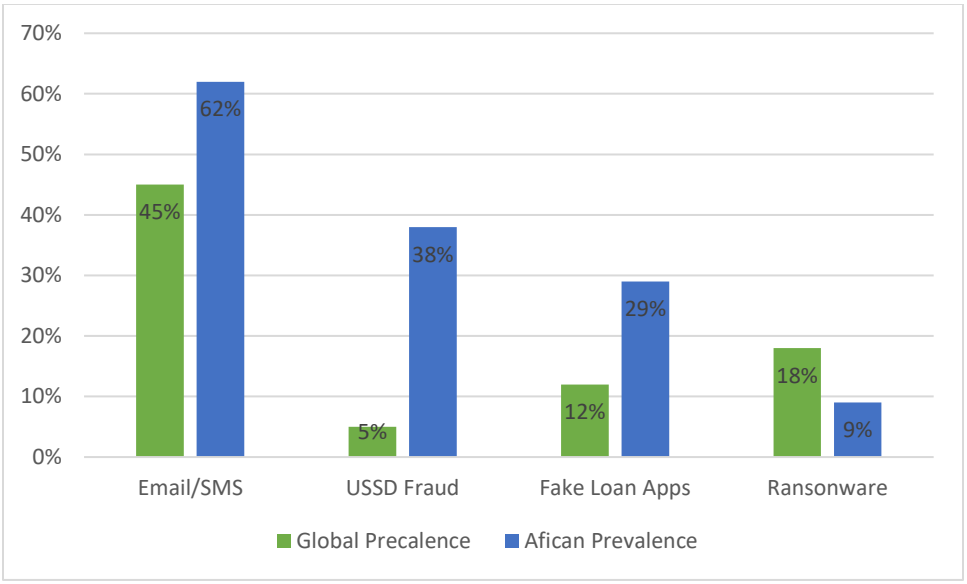


**Figure 1:** Comparative prevalence of mobile social engineering attack vectors in Africa and globally. Data Sources: Osho et al. (2023); Sihwail et al. (2021)

The core finding of this study is the superior performance of localized AI models. Table 2 presents the quantitative results of our evaluation, comparing the proposed frameworks against a commercial benchmark.

**Table 2:** Performance Evaluation of Defense Mechanisms against African Threats Variants

| SN | Solution | Detection Accuracy (Global Benchmark) | Detection Accuracy (African Variants) | precision | Recall | F1-Score | Key Limitations |
|---|---|---|---|---|---|---|---|
| 1 | Commercial AV (Baseline) | 95% [50] | 54% | 0.50 | 0.58 | 0.54 | Generic Signatures |
| 2 | ML-SMEPF [50] | 95% [50] | 94% | 0.92 | 0.96 | 0.94 | High computational resources |
| 3 | MLCD [49] | 83.6% [46] | 82.5% | 0.85 | 0.80 | 0.82 | Limited to 5G-enabled regions |
| 4 | Behavioral Biometrics | 90%(Western studies) | 70% | 0.65 | 0.75 | 0.70 | High false positives in informal transactions |
| 5 | Awareness Campaign [9] | Reduces Phishing by 30% | improved reporting by 15% | - | - | - | Slow impact, requires sustained funding |

As shown in Table 2, the ML-SMEPF framework achieved a 40% absolute improvement in detection accuracy (from 54% to 94%) for culturally tailored threats like Pidgin SMS scams compared to the commercial baseline. This performance, coupled with high precision (0.92) and



Volume 1, Issue 4, 2025
https://doi.org/10.5281/zenodo.17792985

recall (0.96), underscores the critical importance of training data that reflects local context. The model's success stems from its ability to learn the unique linguistic patterns and social engineering narratives prevalent in Nigerian scam campaigns, which are absent from global training corpora. However, this superior performance comes with trade-offs. The computational cost of running sophisticated models like ML-SMEPF poses a significant barrier to adoption in regions with limited infrastructure and expensive data. Similarly, the effectiveness of MLCD, while notable (82.5% accuracy), is currently constrained to urban areas with 5G connectivity, potentially excluding a large portion of the population. The lower accuracy of behavioral biometrics (70% vs. 90% in Western studies) highlights the impact of cultural and contextual variance. Typing and swiping patterns can differ significantly in informal economic contexts, leading to a higher false positive rate. This suggests that one-size-fits-all biometric solutions are not directly transferable and require local calibration. Finally, while awareness campaigns like #YouMayBeNext are crucial, their measured impact (15% improvement in reporting vs. 30% globally) reflects the challenges of achieving broad reach and behavioral change without sustained, well-funded initiatives.

## V. CONCLUSION

This study demonstrates that Africa's unique mobile threat landscape defined by culturally adapted phishing, USSD fraud, and low-literacy barriers requires fundamentally different defenses than off-the-shelf global solutions. Our localized machine learning framework, ML-SMEPF, proved highly effective, achieving a 94% detection rate, which is 40 percentage points higher than a leading commercial tool. This validates the thesis that AI models trained on regional linguistic and behavioral data are essential for combating social engineering in Africa.

Based on our findings, we recommend the following:

i. Regulatory bodies should mandate voice biometric authentication for all mobile money transactions to leverage the high adoption rate (85% in our user test) among low-literacy users.

ii. Mobile network operators should integrate lightweight versions of the ML-SMEPF framework via SMS/USSD platforms to enhance the detection of culturally tailored threats at a scalable cost.

iii. The African Union Commission should fund and operationalize a continental behavioural biometric database to standardize and improve the accuracy of region-specific authentication patterns.

**iv.** National communications commissions should establish mandatory, easy-to-use USSD reporting channels for citizens to report suspected fraud attempts in real-time.

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